

# Math 170S: Homework 1

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**Problem 1.**  $f(x) = \frac{\lambda^x}{x!} e^{-\lambda}$   $P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = P(X_1 = x_1)P(X_2 = x_2) \dots P(X_n = x_n)$  by independence. Thus,  $L(x_1, x_2, \dots, x_n, \lambda) = \prod_{i=1}^n \frac{\lambda^{x_i}}{x_i!} e^{-\lambda}$ .

$\log$  preserves maximization, so  $\arg \max_{\lambda} L(x_1, x_2, \dots, x_n, \lambda) = \arg \max_{\lambda} \log(L(x_1, x_2, \dots, x_n, \lambda))$ .

$$\arg \max_{\lambda} L(x_1, x_2, \dots, x_n, \lambda) = \sum_{i=1}^n \log\left(\frac{\lambda^{x_i}}{x_i!} e^{-\lambda}\right) = \sum_{i=1}^n x_i \log(\lambda) - \log(x_i!) - \lambda \frac{\partial L}{\partial \lambda} = 0 = \sum_{i=1}^n \frac{x_i}{\lambda} - 1 \Rightarrow$$

$$\hat{\lambda} = \frac{\sum_{i=1}^n x_i}{n} = \bar{x}$$

We know  $L(\hat{\lambda})$  is a maximum by the second derivative test  $\frac{\partial^2 L}{\partial \lambda^2} = \sum_{i=1}^n -\frac{x_i}{\lambda^2} < 0$  because the  $x_i$ s are positive and any number squared is positive.

**Problem 2.** For 5 heads and 25 tails  $L(X_1 = x_1, X_2 = x_2, \dots, X_{30} = x_{30}, p) = \prod_{i=1}^{30} p^{x_i} (1-p)^{1-x_i}$  for  $x_i \in \{0, 1\}$ .

$$\arg \max_p L(p) = \sum_{i=1}^{30} x_i \log(p) + (1-x_i) \log(1-p) \frac{\partial L}{\partial p} = 0 = \sum_{i=1}^{30} \frac{x_i}{p} - \frac{1-x_i}{1-p} = \frac{5}{p} - \frac{25}{1-p} \Rightarrow 5(1-p) =$$

$$25p \Rightarrow \hat{p} = \frac{1}{6}$$

We know  $L(\hat{p})$  is a maximum by the second derivative test  $\frac{\partial^2 L}{\partial p^2} = -\frac{5}{p^2} - \frac{25}{(1-p)^2} = -216 < 0$

**Problem 3.** 1. WTS  $f(x|y, \theta) \geq 0$  for all  $x$  and  $\int_y^\infty f(x|y, \theta) dx = 1$  (using  $x \geq y$ .)

$f(x|y, \theta) = \theta y^\theta x^{-\theta-1}$ .  $\theta$  and  $y$  are both positive, so  $\theta y^\theta > 0$ .  $x \geq y > 0$ , so  $x > 0$ . A positive number raised to any power is positive, so  $x^{-\theta-1} > 0$ . Hence,  $\theta y^\theta x^{-\theta-1} > 0$  for all  $x$ .

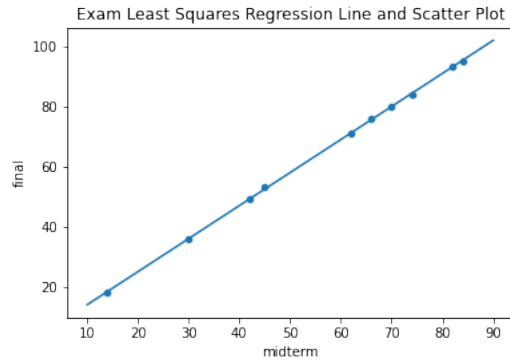
$$\int_y^\infty \theta y^\theta x^{-\theta-1} dx = -y^\theta x^{-\theta} \Big|_y^\infty = -y \lim_{x \rightarrow \infty} x^{-\theta} - (-y^\theta x^{-\theta}) = 1 \quad (\theta > 1)$$

2.  $L(\theta) = \prod_{i=1}^n \theta y^\theta x_i^{-\theta-1}$   $\arg \max_{\theta} L(\theta) = \arg \max_{\theta} \log(L(\theta)) = \sum_{i=1}^n \log(\theta) + \theta \log(y) - (\theta+1) \log(x_i)$ .

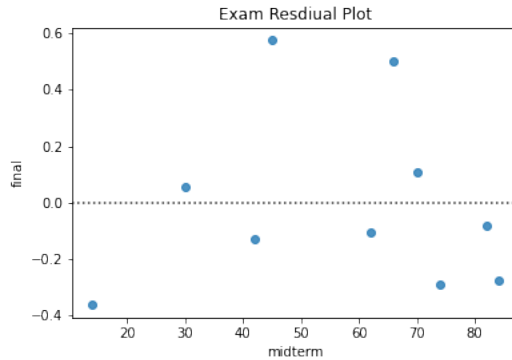
$$\frac{\partial L}{\partial \theta} = 0 = \sum_{i=1}^n \frac{1}{\theta} + \log(y) - \log(x_i) \Rightarrow \frac{n}{\theta} = \sum_{i=1}^n \log\left(\frac{x_i}{y}\right) \Rightarrow \hat{\theta} = \frac{n}{\sum_{i=1}^n \log\left(\frac{x_i}{y}\right)}$$

We know  $L(\hat{\theta})$  is a maximum by the second derivative test  $\frac{\partial^2 L}{\partial \theta^2} = -\frac{n}{\theta^2} < 0$  because the square of any number is positive and a negative times a positive is negative.

**Problem 4.** 1.  $\beta_1 = \frac{\text{cov}(x,y)}{s_x^2} = \frac{\sum (y - \bar{y})(x - \bar{x})}{\sum (x - \bar{x})^2} = 1.09878929, \beta_0 = \bar{y} - b\bar{x} = 2.9788896$



2.



3. The residuals from the Midterm vs. Final plot don't follow a trend (points are randomly distributed above and below the regression line). This implies a linear regression fits the data well.

$$4. L(\beta_0, \beta_1, \sigma^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_i - (\beta_0 + \beta_1 x_i))^2}{2\sigma^2}\right). \quad \arg \max_{\sigma^2} L(\sigma^2) = \log(\arg \max_{\sigma^2} L(\sigma^2)) =$$

$$\sum_{i=1}^n -\frac{1}{2} \log(2\pi) - \frac{1}{2} \log(\sigma^2) - \frac{(y_i - (\beta_0 + \beta_1 x_i))^2}{2\sigma^2} \quad \frac{\partial L}{\partial \sigma^2} = 0 = \sum_{i=1}^n -\frac{1}{2\sigma^2} + \frac{(y_i - (\beta_0 + \beta_1 x_i))^2}{2(\sigma^2)^2} \Rightarrow$$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2}{n}$$

We know  $L(\hat{\sigma}^2)$  is a maximum by the second derivative test  $\frac{\partial^2 L}{\partial (\sigma^2)^2} = \frac{n}{2(\sigma^2)^2} - \frac{\sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2}{(\sigma^2)^3} =$

$$\frac{n}{2(\sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2)^2} - \frac{n^3}{(\sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2)^2} < 0 \text{ because } n^3 > \frac{n}{2} \text{ for all natural numbers and variance is positive.}$$

**Problem 5.** We need two equations because we have two unknowns.

$$E[X] = \int_0^1 x f(x|\alpha, \beta) dx = \frac{\alpha}{\alpha + \beta} \int_0^1 \frac{\Gamma(\alpha + \beta + 1)}{\Gamma(\alpha + 1)\Gamma(\beta)} x^\alpha (1-x)^{\beta-1} dx = \frac{\alpha}{\alpha + \beta} \int_0^1 \text{beta}(\alpha+1, \beta) dx = \frac{\alpha}{\alpha + \beta}$$

$$E[X^2] = \int_0^1 x^2 f(x|\alpha, \beta) dx = \frac{\alpha(\alpha + 1)}{(\alpha + \beta)(\alpha + \beta + 1)} \int_0^1 \text{beta}(\alpha + 2, \beta) dx = \frac{\alpha(\alpha + 1)}{(\alpha + \beta)(\alpha + \beta + 1)}$$

$$\beta = \frac{(1-E[X])^2}{E[X](E[X^2]-E[X]^2)} \quad \alpha = E[X^2] \frac{1-E[X]}{E[X^2]-E[X]^2}$$